MDT-based Intelligent Route Selection for 5G-Enabled Connected Ambulances

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***Abstract*—The fifth generation of cellular network (5G) can facilitate in-ambulance patient monitoring, diagnosis, and treatment by a remote specialist. However, 5G coverage and link quality can vary in time and location. The ambulance route selection can help meet the communication requirements of the in-ambulance applications. In this paper, we propose an innovative ambulance route selection framework which combines the communication requirements along with the network coverage and resources. The framework leverages the minimization of drive test (MDT) data to estimate the network coverage along the ambulance routes. To address the uneven distribution of location-based user-generated MDT data, we examine the performance and trustworthiness of several interpolation techniques to enrich the global MDT map for route selection. A simulated analysis shows that the proposed framework can dynamically adapt to varying application requirements as well as rapidly changing network conditions such as outages. Results also reveal that nearest neighbor and kriging interpolation techniques help complement the proposed framework by addressing the data sparsity problem.**

***Index Terms*—Connected ambulance, smart routing, MDT report, 5G**

I. Introduction

The utility of connected ambulance can be augmented with better coverage and larger capacity of 5G network combined with the legacy 4G networks [1]. 5G-enabled connected ambulances can provide in-ambulance services such as audio and video-based monitoring, patients vital signs transmission, and remote assistance to the ambulance paramedical staff, while the patient is en route to the hospital. These in-ambulance services can significantly benefit patients in critical conditions such as cardiac arrest and stroke [2].

Legacy approaches to determine the optimal ambulance route only consider the minimum time to reach the hospital [3]. These methods do not consider the ambulance network connectivity along the route. Although minimizing the time to reach the hospital is relevant to non-connected ambulances, it does not address the needs of those that rely on connectivity to execute patient care en-route to the hospital. To fully support the connected in-ambulance treatment, the patient connectivity requirements should also be considered in choosing the optimal ambulance route. Hence, we propose an ambulance route selection framework incorporating both the connectivity needs and ambulance travel time.

To assess the coverage in a certain area, drive testing is the conventional method [4]. This approach is limited by its laborious nature and the high monetary cost of performing drive tests. In addition, the network coverage can rapidly change due to several factors such as change in physical parameters of base station (BS), e.g. antenna tilt, azimuth, and transmit power, BS outage due to natural calamities, hardware or software fault, and the changing environmental conditions. To address these issues, the 3rd Generation Partnership Project (3GPP) has standardized an automated data collection mechanism from the public users through minimization of drive test (MDT) [5]. The MDT report contains the key performance indicators for coverage such as received signal strength by a user along with the geographical location of the user. These MDT reports are sent to the serving BS from the user. MDT reports provide accurate, instant and single spot network condition which eases the process of network coverage estimation and hence, can be utilized for smart ambulance routing algorithm. However, the utility of the MDT based coverage maps is undermined by the uneven distribution of voluntary user-generated MDT reports that vary with locations. In this regard, methods to address the MDT report sparsity are needed for using MDT as coverage maps.

A. Related Work

Several studies in literature proposed smart routing techniques for ambulances. A route selection algorithm based on the service level agreement with the transport network and the energy constraint for service continuity was proposed in [6]. Another study [3] proposed a congestion-aware alternative route for emergency vehicles using combinations of sensory data such as speed of vehicles, emission of CO_2, sound and temperature along the candidate routes and the crowd-sourced data including congestion type, congestion level and congestion duration. The study leveraged this data to design a fuzzy-logic based mechanism for fastest route selection of the emergency vehicle. While the goal of the previous studies was to route an ambulance to a selected hospital, a study [7] focused on routing the ambulance to the best matched hospital in terms of the hospital bed utilization, availability of necessary medical equipment, availability of health personnel, among others. The authors proposed a cooperative game for maximizing the number of cured patients with hospitals acting as players.

On the other hand, several recent studies have explored the solutions for addressing the uneven distribution and the potential use case of MDT data. Authors in [8] used regression clustering to enrich reference signal received power (RSRP) maps from the MDT measurements. A recent study in [9] highlighted several challenges that hinder the full realization of MDT utility and explored several techniques including moving average, inverse distance weighted, nearest neighbor, splines and kriging among others to address the sparsity challenge. In addition, recent studies [10]–[13] have used the MDT data to design mobility management solutions.

The presented literature on ambulance routing aims to reduce the time to the hospital for ambulances. Although good network conditions can be vital in connected ambulances, the current ambulance routing literature does not consider the 5G connectivity needs of the connected ambulance and the patient use-case it serves. Hence, there is a need for an ambulance routing framework that can dynamically adjust to patient requirements and varying network conditions of 5G.

B. Contributions

The main contributions of this work are summarized as follows:

1) This paper presents a novel framework for smart ambulance routing, that leverages MDT based maps and resource utilization of the BS to meet the in-ambulance 5G connectivity requirements. The framework considers both the travel time to the hospital and the in-ambulance 5G requirements to find the optimal ambulance route. In addition, the proposed framework is robust to rapidly changing network conditions such as cell outages and sleeping cells.
2) We formulate the route selection as an optimization problem that can adjust the solution according to the in-ambulance connectivity needs. This flexibility allows the optimization problem to meet various ambulance requirements such as: (1) fastest route without 5G connectivity constraints, (2) fastest route with 5G coverage constraint, and (3) fastest route with 5G coverage and capacity constraints.
3) We show the adverse affect of uneven distribution of MDT data on the ambulance route selection framework. To mitigate the adverse impact of spares MDT coverage maps on the proposed framework, we investigate several interpolation techniques to enrich the coverage maps. We observe that the nearest neighbor and kriging outperform other interpolation techniques for the use cases explored in this work.
4) We perform an extensive performance evaluation to test the proposed framework for different ambulance connectivity needs and network conditions. The analysis reveals that the proposed framework can better meet 5G connectivity requirements compared to shortest time only routing approaches even with BS outages.

II. Proposed Framework and Problem Formulation

This section presents the proposed framework for the intelligent ambulance routing that utilizes MDT based RSRP maps. We also formulate the optimization problem for the ambulance route that meets both the ambulance and the patient constraints.

A. Proposed Framework

The proposed framework for intelligent ambulance routing is shown in Fig. 1. The routing algorithm is the major block of the proposed framework. The algorithm works for each ambulance individually and decides the optimal route from the patient location to the hospital when the patient boards the ambulance. The algorithm requires the ambulance start point, target hospital location, type of ambulance service, resource utilization of the base stations, geographic maps and RSRP coverage maps of the surrounding areas. The framework can either work at a central location where all this information is made available or at the ambulance itself.

The intelligent ambulance routing algorithm block can be further divided into the optimization problem generator and the route finding algorithm. The optimization problem generator formulates the optimization problem considering the ambulance connectivity demands on the 5G network. These demands can include the coverage requirement along the ambulance route, the capacity or physical resource block (PRB) requirement or both as described in sub-section II-B. The framework assumes that some ambulances use 5G connectivity only to transmit patients' vital signs and support audio-based communication. Meanwhile, other ambulances that are equipped with video-based monitoring and communication capabilities would exhibit higher demand for capacity together with a more stable 5G connection to support video-based services.

Once the optimization problem is formulated, the intelligent route finding algorithm considers the other input parameters to determine the optimal ambulance route. These parameters include, patient location, target hospital location, geographic maps, RSRP maps and resource utilization of BS. The patient location and the target hospital provide the starting and the ending point for the ambulance route. The patient and hospital locations are also used to get the geographic maps of the surrounding areas from third party services such as Google maps. These geographic maps are used to extract several possible ambulance routes between the patient and the target and choose the best route from these available routes, which meets the ambulance connectivity requirements. Another utility of the geographic map is to set the boundary when constructing the RSRP maps. The MDT data can be used to construct the the RSRP maps in the area of interest. This MDT reporting has been standardized by 3GPP for easier network coverage estimation. The framework can get the MDT based RSRP map as well as the traffic load status of each BS from network operators, which can be a part of service level agreement with the network operator. The public users report the MDT data periodically and contains the RSRP of the user. We utilize these RSRP values from MDT reports to construct a coverage map of the geographical area. However, these MDT reports are spatially unevenly distributed. Thus, we incorporate a data enrichment block to mitigate the impact of data sparsity and generate enriched MDT based RSRP maps. The intelligent route finding algorithm leverages these enriched RSRP maps to include stable 5G coverage in the routing decision. The inclusion of RSRP maps in the algorithm also makes it robust against network outages and faults by avoiding the routes with bad RSRP conditions. Additionally, we leverage the resource utilization block to extract the current PRB utilization of each BS in the geographic area of interest. The intelligent route

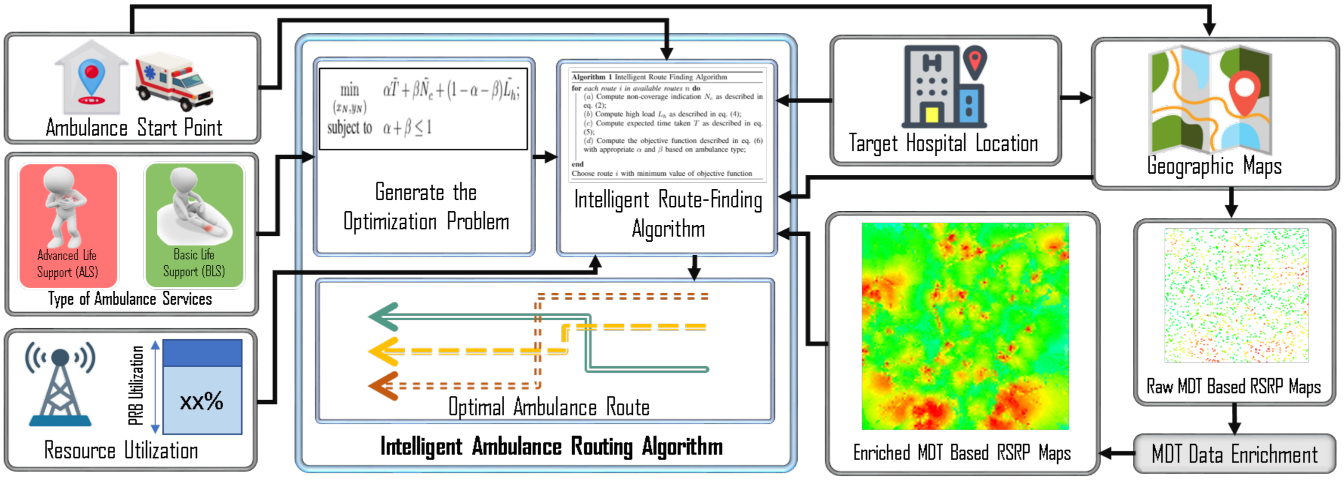

Fig. 1. Proposed framework for MDT based intelligent ambulance routing

finding algorithm exploits the resource utilization information to choose such a route wherein all the serving BS have enough residual resources to support the services of the ambulance. A detailed description of the intelligent route finding algorithm is presented in section III.

B. Problem Formulation

This subsection formulates the optimization problem and details the optimization problem generator. We use the RSRP from the serving cell as a coverage indication for the ambulance. To meet the coverage requirement along the ambulance route, the historical RSRP in each transmission time interval (TTI) should be higher than the required RSRP threshold. A set $\mathbb{R}$ containing possible ambulance routes is obtained from third party services. We define a non-coverage indicator C_i for a specific route i, which denotes the percentage of TTIs with RSRP of ambulance less than the required RSRP threshold. This RSRP threshold can be set based on the ambulance service. C_i can be expressed as:

$$C_i = \frac{1}{|\mathbb{T}^i|} \sum_{\forall t \in \mathbb{T}^i} \mathbb{1}[\eta_t^s < \eta_{th}] \times 100\% \tag{1}$$

where $\mathbb{1}[.]$ is the indicator function, η_t^s is the RSRP from the serving BS s in the TTI t to the ambulance, η_{th} is the minimum RSRP threshold required by the ambulance and the set $\mathbb{T}^i$ contains all the TTIs from the ambulance's starting location to the ambulance's ending location along a specific route i. The length of $\mathbb{T}^i$ can vary for each distinct ambulance route because each route has a different travel time.

Meanwhile, the number of unallocated PRBs in a TTI t at each BS along the ambulance route can be allocated to the ambulance. We define residual PRBs $N_{s,t}^r$ during TTI t at the BS s as the number of unallocated PRBs and can be written as:

$$N_{s,t}^r = N_s - \sum_{\forall u \in \mathbb{U}^s} N_{u,t}^s \tag{2}$$

where N_s is the total number of PRBs at a BS s, $N_{u,t}^s$ is the number of PRBs allocated to user u at TTI t connected to BS s, and the set $\mathbb{U}^s$ contains all the users connected to the BS s. This residual PRBs for all BS along the ambulance route should be statistically greater than the PRBs required by the ambulance. We define the high load scenario as the percentage of TTIs wherein the residual PRBs of the ambulance-serving BS is than the PRBs required by the ambulance. The high load L_i condition for an ambulance route i can be written as:

$$L_i = \frac{1}{|\mathbb{T}^i|} \sum_{\forall t \in \mathbb{T}^i} \mathbb{1}[N_{s,t}^r < N_a] \times 100\% \tag{3}$$

where $N_{s,t}^r$ is the residual PRB at the ambulance-serving BS s in TTI t, and N_a is the sum of PRBs required by all ambulance services. We assume that the ambulance will know the PRBs required for each in-ambulance service. As a first step towards including network performance in the ambulance route selection decision, we consider RSRP and residual PRBs as metrics of the network performance. We acknowledge that other performance metrics can be included. However, these two metrics provide a proof of concept for the proposed framework.

Lastly, the expected time taken T_i for route i by the ambulance to travel from the patient's location to the hospital can be written as:

$$T_i = T_{E,i} - T_{S,i} \tag{4}$$

where $T_{E,i}$ and $T_{S,i}$ are the travel ending time and starting time in seconds for a route i, respectively. Because sophisticated modeling of the expected ambulance travel time is not the major objective of this paper, we model the time taken to reach the hospital by varying the ambulance speed on different segments of the ambulance route. However, the system model and the proposed framework has the flexibility to incorporate more sophisticated time estimation models such as Google maps [14].

An ambulance route jointly optimizing the time taken to reach the hospital, the non-coverage indication and the high load can be chosen. The optimization problem for this can be expressed as:

$$\begin{aligned} \underset{i}{\text{argmin}} \quad & \alpha \tilde{T}_i + \beta \tilde{C}_i + (1-\alpha-\beta)\tilde{L}_i; \\ \text{subject to} \quad & \alpha + \beta \leq 1 \end{aligned} \tag{5}$$

where $\tilde{T}_i$ is the normalized values of T_i between 0 and 100, α, β and $(1-\alpha-\beta)$ are the weights for T_i, C_i and L_i, respectively. The normalization is done to remove the bias towards the higher values of T_i.

III. Solution Methodology

In this section, we present the solution for different blocks of the proposed framework to find the optimal ambulance route. Particularly, we discuss the different techniques for enriching the RSRP maps, the generation of the optimization equation, and the intelligent routing algorithm to find the optimal ambulance route.

A. Enriching the RSRP Maps

The RSRP maps through MDT data are usually unevenly distributed in space due to the absence of MDT reports from random locations where no users report MDT data in the scheduled frame. As a result, the ambulance routing algorithm cannot certainly perceive the overall RSRP condition along the ambulance route. Using the raw MDT based RSRP maps can lead to a non-optimal ambulance path especially if the missing MDT data along the ambulance path have poor RSRP values. To resolve this problem, several techniques can be leveraged to construct the complete RSRP maps by interpolating the missing RSRP values from the neighboring geographical bins. We utilize five different techniques, named moving average, inverse distance weighted, nearest neighbor, splines, and kriging, to interpolate the missing RSRP values [8], [9], [15].

B. Generation of the Optimization Equation

The routing algorithm should have the flexibility to address different ambulance and patient requirements. The design of the optimization equation presented in (5) provides this flexibility. The values of α and β enable a customized optimization equation that can meet the ambulance and patient requirements. Although the array of possible in-patient conditions can be numerous, in this paper, we use three use cases with varying ambulance requirements to evaluate the proposed framework. These use cases are discussed as follows:

1) Ambulance Case A: The scenario in which the only priority is reaching the hospital as fast as possible. For this case, we set $\alpha = 1$ and $\beta = 0$ in eq. (5) to provide the highest importance to time the ambulance will take to reach the hospital.

2) Ambulance Case B: Patient in the ambulance requires services that depend on good 5G coverage for low-load transmission such as audio monitoring, and vital sign transmission. Hence, we set $\alpha = 0.5$ and $\beta = 0.5$ in eq. (5) to give equal weights to the time the ambulance will take to reach the hospital and the non-coverage indication. Doing so makes sure that both the coverage and the travel time to the hospital are considered in the ambulance routing algorithm.

3) Ambulance Case C: Ambulance Case C carries patients with conditions requiring a good coverage and high capacity such as high quality video monitoring. For this case, we set $\alpha = 0.33$ and $\beta = 0.33$ in eq. (5) providing equal weights to time duration going to the hospital, non-coverage indication, and high load.

Algorithm 1 Intelligent Route Finding Algorithm

for *each route i in available routes $\mathbb{R}$* **do**
- (a) Compute non-coverage indication C_i as described in eq. (1);
- (b) Compute high load L_i as described in eq. (3);
- (c) Compute expected time taken T_i as described in eq. (4);
- (d) Compute the objective function described in eq. (5) with appropriate α and β based on ambulance type;

end

Choose route i with minimum value of objective function

C. Intelligent Route Finding Algorithm

The routing algorithm leverages the enriched RSRP maps and the optimization equation for different ambulance use cases to find the best route that meets the ambulance requirements. The major steps of the optimal route-finding scheme are summarized in algorithm 1, which starts by examining each route i from a set of available routes $\mathbb{R}$. The set of available routes can be chosen from third party services such as Google maps. For each route i, the algorithm calculates non-coverage indication C_i leveraging the enriched RSRP maps, high load L_i, and the expected travel time by the ambulance to reach the hospital T_i. The algorithm then computes the value of the objective function based on the values of α and β defined in sub-section III-B. Once the objective function is determined for all the available routes, the algorithm chooses the optimal route with the minimum objective function value. If multiple routes with same time are available, the route finding algorithm will choose the route with the lowest value of objective function. For ambulance case B and C, the algorithm will trade off a longer ambulance time in favor of better network performance if the shortest route does not have best coverage and load indication among all paths. This will delay the patient's arrival in the hospital for ambulance case B and C. Hence, it is important to choose ambulance case A for patients if reaching to the hospital is the single most important factor.

IV. Performance Evaluation

In this section, we evaluate the performance of the proposed intelligent optimal route-finding algorithm for varying ambulance cases and network conditions through simulation. We also analyze the impact of raw MDT based RSRP maps on the optimal ambulance route and the utility of different interpolation methods in enriching the raw MDT-based RSRP maps.

A. Simulation Setup

We deploy a 5G new radio network consisting of macro and small cells using a ray-tracing based commercial planning tool to generate the MDT data as shown in Fig. 2. In order to deploy a realistic simulation environment, we utilize geographical data including raster data (digital terrain model) and geo vector data for an area in Manhattan, New York. An advanced ray-tracing based model known as aster model is used for pathloss. This model incorporates phenomena such as vertical diffraction over the roof-tops, ray-launching based

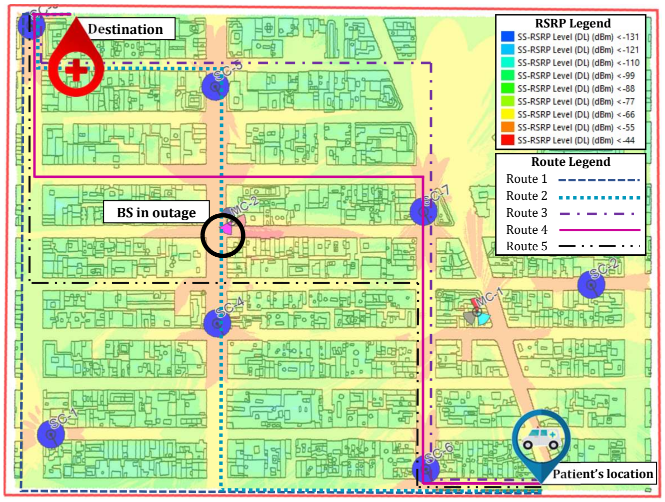

Fig. 2. Simulation setup and ambulance routes

horizontal diffraction/reflection and ray tracing calculation on raster and vector building data. In addition, the shadowing is modeled as a log-normal distribution with varying standard deviation as a function of clutter type. 3D antenna models consisting of horizontal and vertical antenna patterns are used for both macro and small cells. Moreover, we leverage Atoll's automatic cell planning tool (ACP) and industrial domain knowledge for initial site placement and selection of BS parameters such as mechanical antenna tilts, azimuth, and transmitter height. A summary of the simulation parameters is presented in Table I.

The target hospital location and the patient's location are highlighted on Fig. 2. Additionally, Fig. 2 also shows the different possible ambulance routes from the patient's location going to the hospital. To verify the efficacy of the proposed framework for the different ambulance cases presented in subsection III-B, we select five ambulance routes with varying expected travel time, coverage and cell loads also shown in Fig. 2. The simulation scenario can be extended to include additional possible ambulance routes. The optimized BS deployment, user mobility traces and RSRP maps are imported in SyntheticNET [16].

B. Performance Analysis with Network Outages

This subsection analyzes the performance of the proposed framework assuming complete RSRP maps are available. This assumption allows to exhibit the initial feasibility of the framework before considering the more realistic unevenly distributed RSRP maps. Fig. 3 shows the non-coverage indication, high load, and ambulance travel time going to the hospital for all of the five available paths along with the optimal ambulance route for cases A, B, and C. Fig. 3(a) indicates that Route 1 has the minimum travel duration. As a result, the conventional method of minimizing the travel time duration will always take Route 1 without considering the ambulance and patient's connectivity needs. In contrary, the proposed framework can adapt to the varying patient connectivity requirements. While the proposed framework selects Route 1 for case A with shortest travel duration as the only requirement, our solution designates Route 5 and Route 3 for cases B and

TABLE I
DESCRIPTION OF SIMULATION PARAMETERS

Parameter Description	Value
Simulation Area	938m×697m
Number of Sites	Macro Cells (MC): 2; Small Cells (SC): 7
Cell Sectors	MC: Tri-sectored; SC: Omni-directional
Transmission Frequency	MC: 870 MHz; SC: 3300 MHz
Transmission Bandwidth	MC: 10 MHz; SC: 20 MHz
Beamforming Model	MC: 64T64R 90 deg 24dBi Low & Mid-bands; SC: 32T32R 360 deg 17 dBi Mid-band
Pathloss Model	Aster Propagation (Ray-tracing)
Geographical Information	Ground heights, building heights, land use maps
Shadowing	Clutter-dependent shadowing
Geographical Bin Size	1m
Total Active Users	45
TTI	1 ms

C, respectively as shown in Fig.3(a). Given that case B gives equal importance to the travel time duration and the non-coverage indication, it can be observed that Route 5 provides the minimum combination of these two parameters compared to Route 1 and Route 2. These routes, although take shorter time duration, have larger non-coverage indication. Moreover, although Routes 3 and 4 have lesser non-coverage indication compared to Route 5, the shorter travel duration time for Route 5 offsets the small difference in the non-coverage indication. Hence, the proposed framework selects Route 5 as the optimal route for the ambulance case B. On the other hand, case C gives equal importance to time, non-coverage indication and high load with Route 3 providing the best combination of these three as compared to other routes.

The results in Fig. 3(b) illustrate the robustness of the proposed system against network outages. Fig. 3(b) shows the optimal routes for the three ambulance use cases when one macro cell sector (MC2-3) shown in Fig.2 is in outage. Increase in the non-coverage indication is evident for Routes 1, 2, and 5 while it remained unchanged for Routes 3 and 4. This happens because one of the best BS for the ambulance traversing Routes 1, 2, and 5 is MC2-3 and after the outage of MC2-3, the next best BS does not meet the RSRP threshold for a fraction of the ambulance course. Moreover, the non-coverage indication is unchanged for Routes 3 and 4 because the ambulance does not connect to MC2-3 for these routes and hence outage of MC2-3 has no impact on the non-coverage indication. It can also be observed that the outage in MC2-3 caused the BSs along Routes 2, 3, and 4 to be highly loaded brought by the shift of the users (other than the ambulance) connected to MC2-3 to the other BSs serving these ambulance routes. On the other hand, the load decreased along Routes 1 and 5 because the outage of MC2-3 forced the ambulance to connect with the second best BS with lower PRB utilization. The proposed routing framework takes into account the changes as a result of outages and adjusts the optimal route based on the new coverage and load conditions. Juxtaposition of Fig. 3(a) and 3(b) shows that the framework changes the optimal route for cases B and C to Route 3 and Route 5, respectively with MC2-3 outage compared to Route 5 and Route 3, respectively with no outage. This analysis highlights the robustness of the proposed routing framework

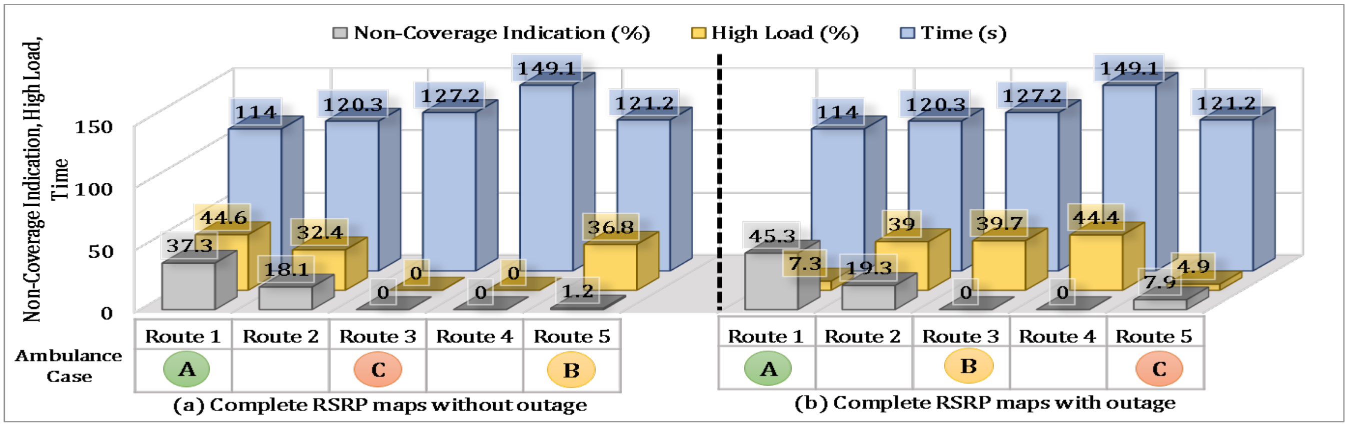

Fig. 3. Performance of the proposed framework with complete RSRP maps

TABLE II
IMPACT OF RAW AND ENRICHED RSRP MAPS ON THE OPTIMAL ROUTE SELECTION. EACH ENTRY REPRESENTS THE NON-COVERAGE INDICATION AND THE BLUE COLORED ENTRY IN EACH ROW SHOWS THE OPTIMAL ROUTE CHOSEN BY THE PROPOSED FRAMEWORK.

		Route 1	Route 2	Route 3	Route 4	Route 5
Time (s)		114	120.3	127.2	149.1	121.2
C_i (%)	**Ground Truth**	37.3	18.1	0	0	**1.2**
	Raw Maps	26.9	**0**	0	0	0
	Moving Average	0.3	**0**	0	0	0
	Inverse Distance	27.1	13.8	3.4	0	**0**
	Nearest Neighbor	32.9	16.1	2	1.1	**1.8**
	Splines	75.7	66.1	48.9	50.2	**47.6**
	Kriging	32.3	14.2	1.8	0	**0**

against dynamically changing 5G network conditions.

C. Performance Analysis with Raw and Enriched RSRP Maps

After demonstrating the feasibility of the proposed framework utilizing the complete RSRP maps, in this subsection, we evaluate the impact of practically available raw MDT based RSRP maps on the ambulance routing. We also analyze the utility of several interpolation techniques in enriching the raw RSRP maps and the performance of the proposed framework with the enriched RSRP maps. Table II shows the impact of raw MDT RSRP maps on the output of the framework and compares different interpolation techniques in mitigating the adverse impact of sparsity. Here, we are only highlighting the ambulance case B because meeting the RSRP requirements is most desired in this case compared to other cases. It is observed that the framework selects Route 2 as the optimal route with raw maps while Route 5 is the actual optimal path for the ambulance. This happens because numerous RSRP values along the routes are missing due to sparsity and the algorithm makes a decision based only on the available RSRP values. These available RSRP values are higher than the RSRP threshold and thus indicate zero non-coverage indication along Routes 2, 3, 4 and 5 with raw RSRP maps. A comparison of the interpolation techniques shows that moving average technique failed to determine the optimal route while inverse distance, nearest neighbor, splines and kriging successfully mitigated the impact of sparsity and managed to select the optimal route. However, although the four interpolation techniques successfully choose the optimal route, an analysis of the non-coverage indication C_i provides a deeper understanding of the utility of these techniques. Table II shows that the values of C_i using nearest neighbor and kriging are closer to the ground truth as compared to other techniques. For instance, the values of C_i for Route 1 generated through nearest neighbor and kriging are 32.9 and 32.3, respectively and these values are closer to the ground truth value of 37.3 compared to other techniques. This trend is also observed for other ambulance routes. This highlights that nearest neighbor and kriging perform better in mitigating the impact of sparsity for the network settings considered in this work and can be used in the proposed framework for enriching RSRP maps. However, the choice of interpolating technique will vary for different geographical locations and network settings.

V. CONCLUSION

This paper presents a framework for ambulance routing that considers both the travel time going to the hospital and the network connectivity requirements in the routing decision. We utilize MDT-based RSRP maps to estimate the coverage along the different ambulance routes. A performance analysis shows that the proposed framework can dynamically adjust based on patient requirements and chooses the route that best meets the in-ambulance connectivity needs. In addition, the proposed framework is robust to rapidly changing network conditions such as cell outages. We also show that the uneven distribution of the MDT data can adversely impact the performance of the proposed framework. To address this issue, we utilize several interpolation techniques to enrich the raw RSRP maps. The results indicate that nearest neighbor and kriging are best suited to mitigate the impact of sparsity for ambulance routing use case presented in this paper.

REFERENCES

[1] H. N. Qureshi, M. Manalastas, S. M. A. Zaidi, A. Imran, and M. O. Al Kalaa, "Service Level Agreements for 5G and Beyond: Overview, Challenges and Enablers of 5G-Healthcare Systems," *IEEE Access*, 2020.

[2] A. V. Espinoza, R.-J. Van Hooff, A. De Smedt, M. Moens, L. Yperzeele, K. Nieboer, I. Hubloue, J. De Keyser, A. Convents, H. F. Tellez, *et al.*, "Development and pilot testing of 24/7 in-ambulance telemedicine for acute stroke: prehospital stroke study at the Universitair Ziekenhuis Brussel-Project," *Cerebrovascular diseases*, vol. 42, no. 1-2, pp. 15–22, 2016.

[3] R. R. Rout, S. Vemireddy, S. K. Raul, and D. V. Somayajulu, "Fuzzy logic-based emergency vehicle routing: An IoT system development for smart city applications," *Computers & Electrical Engineering*, vol. 88, p. 106839, 2020.

[4] B. Sayrac, J. Riihijärvi, P. Mähönen, S. Ben Jemaa, E. Moulines, and S. Grimoud, "Improving coverage estimation for cellular networks with spatial bayesian prediction based on measurements," in *Proceedings of the 2012 ACM SIGCOMM workshop on Cellular networks: operations, challenges, and future design*, pp. 43–48, 2012.

[5] 3rd Generation Partnership Project (3GPP) Technical Specification Group Radio Access Network, "Universal Terrestrial Radio Access (UTRA) and Evolved Universal Terrestrial Radio Access (E-UTRA); Radio Measurement Collection for Minimization of Drive Tests (MDT); Overall Description; Stage 2," in *3GPP TS 37.320 version 16.8.0 Release 16*, March 2022.

[6] A. Sharma and R. Kumar, "Service-level agreement—energy cooperative quickest ambulance routing for critical healthcare services," *Arabian Journal for Science and Engineering*, vol. 44, no. 4, pp. 3831–3848, 2019.

[7] A. Smirnov and N. Teslya, "Ambulance Vehicle Routing under Pandemic with Fuzzy Cooperative Game via Smart Contracts," in *VEHITS*, pp. 538–545, 2021.

[8] F. Sohrabi and E. Kuehn, "Construction of the RSRP map using sparse MDT measurements by regression clustering," in *2017 IEEE international conference on communications (ICC)*, pp. 1–6, IEEE, 2017.

[9] H. N. Qureshi, A. Imran, and A. Abu-Dayya, "Enhanced MDT-Based Performance Estimation for AI Driven Optimization in Future Cellular Networks," *IEEE Access*, vol. 8, pp. 161406–161426, 2020.

[10] M. U. B. Farooq, M. Manalastas, W. Raza, A. Ijaz, S. M. A. Zaidi, A. Abu-Dayya, and A. Imran, "Data driven optimization of inter-frequency mobility parameters for emerging multi-band networks," in *GLOBECOM 2020-2020 IEEE Global Communications Conference*, pp. 1–6, IEEE, 2020.

[11] M. Manalastas, M. U. B. Farooq, S. M. A. Zaidi, A. Abu-Dayya, and A. Imran, "A data driven framework for inter-frequency handover failure prediction and mitigation," *IEEE Transactions on Vehicular Technology*, 2022.

[12] M. U. B. Farooq, M. Manalastas, W. Raza, S. M. A. Zaidi, A. Rizwan, A. Abu-Dayya, and A. Imran, "A data-driven self-optimization solution for inter-frequency mobility parameters in emerging networks," *IEEE Transactions on Cognitive Communications and Networking*, 2022.

[13] M. U. B. Farooq, M. Manalastas, S. M. A. Zaidi, A. Abu-Dayya, and A. Imran, "Machine learning aided holistic handover optimization for emerging networks," in *2022 IEEE International Conference on Communications (ICC)*, IEEE, 2022.

[14] A. Derrow-Pinion, J. She, D. Wong, O. Lange, T. Hester, L. Perez, M. Nunkesser, S. Lee, X. Guo, B. Wiltshire, *et al.*, "Eta prediction with graph neural networks in google maps," *arXiv preprint arXiv:2108.11482*, 2021.

[15] N. Perpinias, A. Palaios, J. Riihijärvi, and P. Mähönen, "A measurement-based study on the use of spatial interpolation for propagation estimation," in *2015 IEEE International Conference on Communications (ICC)*, pp. 2715–2720, IEEE, 2015.

[16] S. M. A. Zaidi, M. Manalastas, H. Farooq, and A. Imran, "SyntheticNET: A 3GPP compliant simulator for AI enabled 5G and beyond," *IEEE Access*, vol. 8, pp. 82938–82950, 2020.